# WSN power management with battery capacity estimation

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# WSN Power Management with Battery Capacity Estimation

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***Abstract*— Wireless sensor nodes are now cheap and reliable enough to be deployed in different environments. However, their limited energy capacity limits their lifespan. In this paper, a Management strategy at network-level of a set of nodes is implemented, taking into account an estimation of the remaining energy in each sensor node. The control formulation is based on Model Predictive Control with constraints and binary optimization variables, leading to a Mixed Integer Quadratic Programming problem. The estimation of the remaining energy in batteries must be simple enough to be implemented in low-cost, low-power, low-computational-capability sensor nodes.**

## I. INTRODUCTION

Wireless sensor networks (WSNs) consist of a large number of sensor nodes (SNs) with sensing, wireless communication and computation capabilities used to monitor and/or control the physical world [1]. Usually, SNs are tiny devices with limited energy capacity stored in batteries. They can be placed in different functioning modes, each mode being associated with a given power consumption.

The main drawback of the SNs is their limited energy storage, leading to a limited lifespan for the WSN. The WSN lifespan increase has already been addressed in the literature, from sensor-level [2]–[4] to network-level. [5] provides an overview of these techniques. [6] proposed a lifespan extension via a Power Management strategy at network-level using a Model Predictive Control (MPC) approach. This latter predicts the "system" trajectories over a receding horizon, while calculating an optimal control policy with respect to a set of constraints [7]. The control problem is formulated as a Mixed Integer Quadratic Programming (MIQP) problem [8]. [6] supposes that the remaining energy in the SN battery is known at each decision time. Basically, the battery capacity measures the charge stored in the battery; it is determined by the mass of active material contained in the battery. However, while sensors accurately measure the gasoline level in a tank, there is no simple sensor available to measure the remaining energy in a battery. Instead, the battery State-of-Charge (SoC) is estimated from other measurements. Different SoC estimation methods are reported, e.g. ampere-hour counting, OCV-based estimation, model-based estimation (Kalman filtering) and other [9], [10]. Note that these approaches deal with relatively "large" battery packs for laptops and electrical vehicles. Their implementation in SNs with limited computational capability is not appropriate.

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Therefore, the main motivation of this paper is to implement, beside the MPC, a remaining energy estimation technique with light computational weight in order to leverage the main hypothesis of [6]. The rest of the paper is organised as follows. Section II deals with system modelling and control objectives. Section III presents the remaining energy estimation method while Section IV is dedicated to the MPC design. Section V reports results on a real testbench.

## II. SYSTEM MODELING AND CONTROL OBJECTIVES

The consumption of the SNs in a WSN is described by:

$$\mathbf{x}_{k+1} = \mathbf{x}_k + B\mathbf{u}_k \tag{1}$$

where $\mathbf{x}_k \in \mathbb{R}^n_+$ is the remaining energy capacity in the batteries of the SNs $S_i$, $i = 1, ..., n$, $n \in \mathbb{N}^*$ at time $k$. The initial battery capacity is denoted $\mathbf{x}_0$. $B\mathbf{u}_k$ represents the energy capacity consumed during the time interval $[kT, (k+1)T]$, where $T$ is the decision period. $\mathbf{u}_k = [\mathbf{u}_1^T, \cdots, \mathbf{u}_i^T, \cdots, \mathbf{u}_n^T]^T \in \{0,1\}^{nm}$ is the control input. $m \in \mathbb{N}^*$ is the number of SN functioning modes. Each sub-vector $\mathbf{u}_i = [u_{i1}, \cdots, u_{ij}, \cdots, u_{im}]^T$ contains the functioning mode of $S_i$, where $u_{ij} \in \{0,1\}$, $j = 1, ..., m$. As $S_i$ has a unique functioning mode at time $k$, a set of constraints must be defined:

$$\forall i = 1 : n, \sum_{j=1}^{m} u_{ij} = 1 \tag{2}$$

Each component $b_{ij}$ of $B_i$ in the control matrix $B = \text{diag}\,[-B_1, \ldots, -B_n] \in \mathbb{R}^{n \times nm}$ represents the amount of energy consumed by $S_i$ working in mode $M_j$ during the decision period $T$. Note that switching from $M_a$ to $M_b$ has an extra cost that is supposed to be integrated in $b_{ib}$.

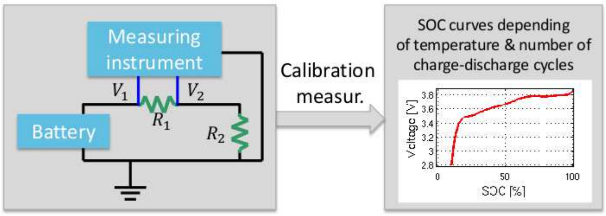
Moreover, the battery energy capacity of $S_i$ is constrained, $0 \leqslant x_k^i \leqslant X_{max}^i$. The remaining capacity in the battery is related to the State-of-Charge (SoC) estimate, expressed as a percentage ($0\%$-*Empty*, $100\%$-*Full*) of some reference.

*Control objectives*

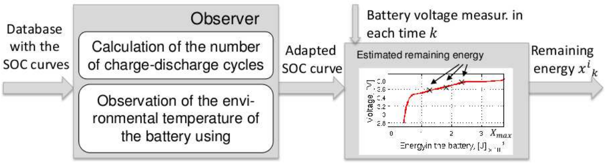
In order to define the system control objectives, the concept of *mission* is introduced. A *mission* is described by the minimum number $d \in \mathbb{N}^*$ of SNs in the active mode, sufficient to provide the requested services and performance level. $d$ may possibly change from time to time. Thus, the *mission* imposes a new constraint:

$$\sum_{i=1}^{n} u_{ij} = d \tag{3}$$

Therefore, the system to be controlled is not only constrained by (2), but also by the set of extra functional constraints (3) that are used to define the *mission*.




(a) Battery calibration




(b) On-line estimation

Fig. 1: Estimation of the remaining energy in a Li-ion battery - 2-steps approach

## III. Capacity Estimation Concept

The battery capacity represents the amount of energy that can be extracted from the battery under certain specified conditions. Battery manufacturers use the concept of State-of-Charge (SoC) to specify the battery performance. The $SoC \in [0, 100]$ (expressed in percent) describes the ratio of the remaining energy $x$ to the nominal capacity $C_{nom} \in \mathbb{R}_+$ of the battery [11]:

$$x = SoC * C_{nom} \tag{4}$$

Thus, a new battery should have a SoC of $100\%$ which corresponds to the nominal battery capacity.

The determination of the SoC for a battery may be a more or less complex problem, depending on the battery type, the chosen estimation method, the requested estimation precision and the application in which the battery is used [9]. According to the analysis of existing SoC estimation methods, here the ampere-hour counting method has been chosen because:

- low-cost sensors for battery calibration are available in laboratories (e.g. current, voltage measurement);
- the computing cost to estimate the SoC is very low;
- the estimation approach can be embedded in any computing element.

The estimation of the remaining energy in the battery of a SN is proposed to be performed in two steps depicted in Fig. 1, namely, a battery calibration step (Fig. 1(a)) and an on-line estimation step (Fig. 1(b)). Both steps are now summarized.

The determination of the remaining energy implemented in the present work is described for Lithium-ion (Li-ion) batteries. However, it can be applied to batteries with other chemistry.

### A. Battery calibration step

The battery calibration is performed off-line during lab. experiments on a new battery for which the SoC is considered equal to $100\%$ (i.e. nominal capacity, taken for data-sheet). When the battery ages, the parameters used to describe the voltage relaxation process become increasingly less accurate. The result is a decrease in the accuracy of the remaining energy estimation. To compensate the ageing effect, the number of charge-discharge cycles and other environmental conditions (e.g. battery environmental temperature) can be taken into account [12]. As a consequence, the estimation accuracy for ageing batteries is almost as high as for new batteries. After each battery charge-discharge cycle, the battery needs to rest for at least four hours to attain its equilibrium and get accurate measurements.

When the nominal battery capacity is known and the current $i(t)$ extracted from the battery can be measured, ampere-hour counting provides an accurate calculation of SoC changes. Here, $i(t)$ is given by (see Fig. 1(a)):

$$i(t) = \frac{V_1 - V_2}{R_1} \tag{5}$$

where $R_1$ is a shunt resistor. This approach can be used for Li-ion batteries because there are no significant side reactions during normal operation [10]. However, for the SoC estimation, the initial SoC $SoC(0)$ must be known:

$$SoC(t) = SoC(0) - \int_0^t \frac{\eta \cdot i(t)}{C_{nom}} \mathrm{d}t \tag{6}$$

$i(t)$ is the instantaneous current (assumed positive for discharge, negative for charge) delivered by the battery, $C_{nom}$ is the nominal battery capacity. The Coulombic efficiency is $\eta = 1$ for discharge, and $\eta \leqslant 1$ for charge.

Using a rectangular approximation for the integration and a sampling period $\Delta t$, a discrete-time approximate recurrence can be derived:

$$SoC_{k+1} = SoC_k - \frac{\eta \cdot \Delta t}{C_{nom}} i_k \tag{7}$$

The measures conducted during the battery calibration phase provide a database with the voltage versus SoC curves (see Fig. 1(a)) depending on the temperature and the battery ageing.

### B. On-line estimation step

The on-line estimation step consists of two sub-steps. The first one selects from the database, built during the calibration step, one SoC curve adapted to the environmental temperature and the number of charge-discharge cycles (related to battery ageing). The second sub-step estimates the remaining energy $x_k^i$ in the battery of SN $S_i$, using the appropriate SoC curve and the voltage measurement at the battery terminals at time $k$. This estimation phase runs together with the control algorithm that is described below.

## IV. Model Predictive Control Design

The minimization of the power consumption of (1) can be seen as a Constrained Optimal Control problem. It can be tackled via a Quadratic Programming (QP) problem. Constrained MPC implies the minimization of a cost function based on the predicted system evolution, under a set of constraints.

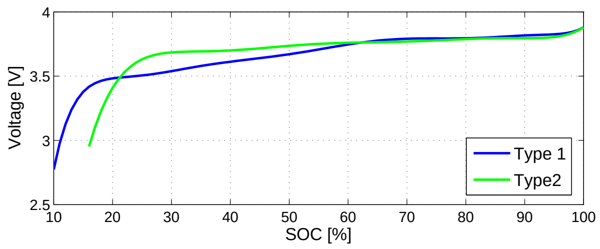



Fig. 2: SoC profiles for two battery types

Recently, the interest in using MPC for controlling systems that involve a mix of real-valued dynamics and logical rules has arisen [13] [14]. However, when the problem formulation leads to an optimization one, the resulting description is no longer a QP problem but a Mixed Integer Quadratic Programming (MIQP) problem with two different types of optimization variables, namely, real-valued and binary ones. This makes this latter problem harder to solve when compared to an ordinary QP problem.

It is assumed throughout the rest of the paper that the pair $(I, B)$ in (1) is stabilizable (recall that the state matrix $A$ is equal to the identity matrix $I$). At each decision time $kT$, the current state (assumed to be available thanks to the method proposed in section III) $\mathbf{x}_k = \mathbf{x}_{k|k}$ is used to define the optimal control sequence $\mathbf{u}^* = \left[\mathbf{u}_{k|k}^T, \ \ldots, \ \mathbf{u}_{k+N_p-1|k}^T\right]^T$ which is solution to the minimization problem:

$$\mathbf{u}^* = \arg\min_u \sum_{i=0}^{N_p-1} \mathbf{x}_{k+i|k}^T Q \mathbf{x}_{k+i|k} + \sum_{i=0}^{N_u-1} \mathbf{u}_{k+i|k}^T R \mathbf{u}_{k+i|k}$$

where:

$$\begin{cases} \mathbf{x}_{k+i+1|k} = \mathbf{x}_{k+i|k} + B\mathbf{u}_{k+i|k}, & i = 1, \ldots, N_p - 1 \\ \mathbf{u}_{k+i|k} = \mathbf{0}, & i = N_u, N_u + 1, \ldots, N_p - 1 \\ \mathbf{u}_{k+i|k} \in \{0, 1\}^{nm} \\ \mathbf{X}_{min} \leqslant \mathbf{x}_{k+i|k} \leqslant \mathbf{X}_{max}, & i = 1, \ldots, N_p - 1 \end{cases} \tag{8}$$

$Q = Q^T \geqslant 0$ and $R = R^T > 0$ are the weighting matrices. $\mathbf{X}_{min}$ and $\mathbf{X}_{max}$ are the lower and upper energy capacity bounds, and the pair $(Q^{1/2}, I)$ is detectable. This minimization problem can be written in an extended form, see [6] for more details.

It is worth mentioning that the degrees of freedom of the control design are related to the choice of the weighting matrices $Q$ and $R$, and the prediction $N_p$ and control $N_u \leqslant N_p$ horizons.

## V. Application

To show the effectiveness of the proposed strategy, a benchmark with $n = 6$ SNs $S_i$, $i = 1, \ldots, 6$, and one sink is considered. At instant $k$, $S_i$ is in a unique mode among 3 possible ones $M_j$, $j = 1, \ldots, 3$:

TABLE I: Power consumption $b_{ij}$ of node $S_i$ in mode $M_j$

| **Sensor node** | **Mode $M_1$** $[mWh]$ | **Mode $M_2$** $[mWh]$ | **Mode $M_3$** $[mWh]$ | **Nom. bat. cap.** $X_{max}^i$ $[mWh]$ |
|---|---|---|---|---|
| $S_1$ | 36.593 | 5.846 | 0 | 3885 |
| $S_2$ | 36.482 | 6.031 | 0 | 3885 |
| $S_3$ | 34.854 | 6.105 | 0 | 3885 |
| $S_4$ | 36.482 | 6.301 | 0 | 3515 |
| $S_5$ | 36.556 | 6.105 | 0 | 3515 |
| $S_6$ | 33.041 | 5.735 | 0 | 3515 |

- $M_1$ is the *Active* mode: the SN works in "duty cycling". This means that it is "off" by default and it enters a wake-up mode periodically with a sampling period $T_s = 1min$ to sense, process and exchange data with the sink;
- $M_2$ corresponds to the *Standby* mode. In this mode, only the external Real Time Clock (RTC) Quartz system is "on". The RTC allows to wake up the SN each $T_w = 1h$ to receive the commands from the sink and monitor the battery remaining energy capacity.
- $M_3$ is the *Faulty* mode. During the network lifespan, some nodes may become unavailable (due to e.g. physical damage, lack of power resources $x_k^i \backslash X_{max}^i \leq \delta_i$) The SN can exit from this mode when for instance, the battery is recharged via a harvesting system $(x_k^i \backslash X_{max}^i > \delta_i)$ or some physical damages are repaired. $\delta_i$ is defined for each battery and depends on its characteristics.

### A. Mission definition

For this application, $n = 6$ SNs are deployed in an open-space office. In order to control the air conditioning unit, temperature and humidity are sensed through the WSN. During the working hours, enough information is collected with 3 SNs to reach the air control objectives. Otherwise, only 1 SN is used to feed the control of the air conditioning unit. Precisely, the *mission* is split in two phases corresponding respectively to working hours and night periods of time. Therefore, the constraints that define the *mission* are dynamically changed, depending on the time schedule, leading to a *dynamic mission*:

| **Time period** | | $d_1$ | **Objectives** |
|---|---|---|---|
| *working hours* | 8am–5pm | 3 | 3 nodes in $M_1$ |
| *Night* | 5pm–8am | 1 | 1 nodes in $M_1$ |

The MPC control law assigns the *Active* mode to certain nodes in order to meet the dynamic *mission* while minimizing the power consumption of the sensor network.

### B. Battery calibration

In this benchmark, two types of Li-ion batteries are used, with nominal capacities $C_{nom} = 3885mWh$ for type 1, and $C_{nom} = 3515mWh$ for type 2. The numerical values are obtained from the technical data sheet [15]. These batteries embed an electronic protection circuit. This latter limits the minimum SoC value (related to the nominal capacity) to 10% for type 1 battery and to 16% for type 2 battery.

The objective of the calibration phase is to build an accurate experimental model of the battery $Voltage - SoC$ curves. Fig. 2 depicts an example of the SoC curves for

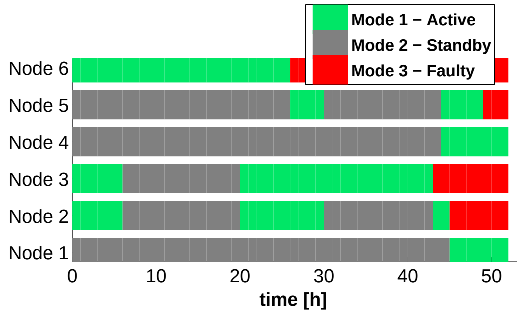



Fig. 3: Functioning modes of sensor nodes vs. time

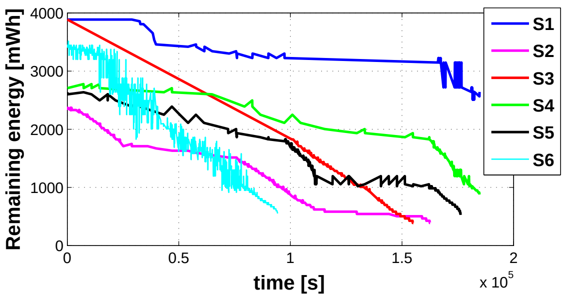



Fig. 4: Estimated remaining battery energy in SN $S_i$

both types of batteries: new batteries at 23°C (ambient temperature in the office) are used. This calibration phase together with the protection circuit allow to safely (without damaging the battery) and efficiently exploit the battery capabilities.

### C. *Choice of the MPC tuning parameters*

For the system (1), the components of matrix $B$ are calculated from the values given in Table I, extracted from the data sheet and lab. measurements for OpenPicus [16] platforms.

The weighting matrices $Q$ and $R$ are chosen equal to:

$$Q = \mathbf{0}_{6\times 6}; \quad R = B^T \times (Ru^T \times Ru)/2 \times B \qquad (9)$$

where $Ru = \operatorname{diag}[ru_1, \cdots, ru_6]$ and $ru_i \triangleq \min\{X^i_{max}/x^i_{k|k}\}$, $x^i_{k|k} \neq 0$. The choice $Q = \mathbf{0}_{6\times 6}$ lies in the fact that the state dynamics should evolve as slowly as possible [17]. The choice of $R$ implies a trade-off between larger power consumption and smaller capacity battery level for node penalization. This choice tries to balance the battery remaining energy capacity in all SNs.

The prediction and control horizons are chosen equal to $N_p = 5$, $N_u = 1$ respectively. As the considered system presents slow dynamics, these horizons seem appropriate. The decision period (i.e. the time period when the power control is run) is $T = T_w = 1h$. Thus, the MIQP problem is solved on-line at each decision time $kT$.

### D. *Experimental Results*

The strategy proposed in this paper is evaluated in real life with an experiment of a duration of 52 hours (starting at $11am$). Beside the MPC strategy, the capacity estimation method proposed in section III is implemented. The experimental results are provided in Figure 3 that shows the functioning modes imposed by the control strategy for each SN. The *mission* during the working hours (resp. the night) can be fulfilled until at least 3 (resp. 1) nodes do not have their batteries drained or have not failed. The estimated remaining battery capacities are given in Figure 4. Due to the different radio channel perturbations the battery discharging behavior is different for each node.

## VI. Conclusions

The implementation of a power management strategy for a WSN together with the estimation of the remaining energy in the battery of sensor nodes is realized. The capacity estimation shows a low computational cost. It consists of two steps. The battery calibration step is carried out off-line during lab. experiments. The on-line estimation step runs besides the control algorithm. Implementation results in a real test-bench show the efficiency of the proposed capacity estimation concept and of the MPC approach implemented.

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